Leadership in Sustainable Infrastructure
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Vancouver, Canada
May 31 – June 3, 2017/ *Mai 31 – Juin 3, 2017*

COMPARATIVE STUDY OF DIFFERENT METHODS FOR NOISE REDUCTION IN THE AMBIENT VIBRATION SIGNAL OF STRUCTURES FOR MODAL IDENTIFICATION

Sabamehr, Ardalan.[1,5], Roy, Timir Baran[2], Mirshafiei, Mehrdad.[3] and Bagchi, Ashutosh[4].
[1,2,4] Concordia University, Canada
[3] Sensequake Inc., Canada
[5] sabamehrardalan875@gmail.com

Abstract: The ambient vibration signals are often very weak and polluted by strong noise which makes modal identification quite challenging. Signal processing algorithms can be used to tackle the problem. In this paper, finite element frame model of a structure is simulated with white Gaussian noise as an ambient excitation. One of the effective methods to reduce the noise level in an ambient vibration signals it to pass it through the Singular Value Decomposition (SVD) algorithm. It can separate the modes in such a way that the topmost curve of SVD has the lowest noise level and bottommost curve has the largest. Additional techniques can be employed to enhance SVD results, such as low-pass filtering and wavelet noise reduction. Therefore, two scenarios have been considered in the finite element model: a combination of low-pass filter and SVD, and Wavelet and SVD. The simulation results are then compared according to the Signal to Noise Ratio (SNR) in SVD. Finally, the techniques have been applied to the vibration test data obtained from the laboratory test on a steel frame.

1 INTRODUCTION

Recently, Vibration Based Damage Detection (VBDD) has attracted considerable attention in Structural Health Monitoring (SHM) applications [Li et al., 2004]. In a structural vibration test, reliability and accuracy of the collected signals is very important, as they are contaminated with noise. The noise embedded in the signal could put limits on detection of small defects by affecting the accuracy and reliability of the results [Yi et al., 2012]. So far, many techniques have been proposed for denoising such signals. Using a low pass filter is the most common method for denoising. Low pass filter has the inherent defect that is not able to reduce or remove the in-band noise; it can only be used for out-of-band denoising. In addition, a single scale representation of signals in the time or the frequency domain is not adequate to separate signal from noisy data [Yi et al., 2012]. Wavelet is a powerful tool to denoise the signal by combining the time and the frequency domain. The advantage of this method is as follows: (1) reduce computational complexity associated with the algorithm; and (2) the ability to provide simultaneously spectral representation and temporal order of the signal decomposition components [Yi et al., 2012]. Donoho and Johnstone (1995) proposed a method known as a wavelet transform shrinkage to estimate unknown smoothed signal from data with noise [Donoho et al., 1995 and Mohl et al., 2003]. Adeli and Kim (2004) discussed about their use of the wavelet transform in structural engineering to eliminate dynamic environmental disturbance signals, or the lower frequency components, from ground acceleration signals of a civil engineering structure, using Daubechies wavelets with three vanishing moments. Adeli and

Jiang (2006) illustrated a signal processing method developed to smoothen the contaminated data of the acceleration response of the structure under earthquakes, based on the discrete wavelet packet transform using a Daubechies wavelet of order 4. Jiang and Mahadevan (2008) also employed the same methodology to remove noise from signals for the nonparametric identification of structures. Rizzo et al. (2005) explained the use of the discrete wavelet transform (db40) for signal denoising in the toneburst signals of very small structures with dimensions less than 1 mm [Kim et al., 2016].

In this paper, the case study is the collected data from vibration test of a three-story steel scale frame. In the test, Low Pass Filter (LPF) and Discrete Wavelet Transform (DWT) have been applied to the signal. Two evaluation metrics have been used including Signal Noise Ratio (SNR) and Root Mean Square Error (RMSE) for individual channel. In a multi-channel measurement, singular value decomposition (SVD) can be employed to evaluate the reduction of noise, as the difference between the largest and the smallest singular values show the SNR in every frequency [Brincker et al., 2015].

2 THEORETICAL BACKGROUND

As displayed in Figure1, the additive Gaussian White noise with certain SNR is added to measured data from accelerometers to generate the noisy signal.

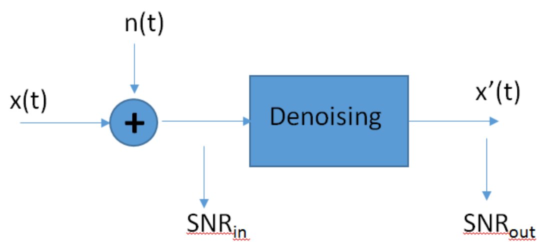


Figure 1: Additive SNR and calculated SNR after denoising

2.1 Low pass Filter (LPF)

Butterworth low pass filter has been selected with the filter order and cut-off values selected depending on the original signals.

2.2 Discrete Wavelet Transform (DWT)

Considering a signal x_n (n = 1,2,...,N) ϵ $L^2(R)$ (L^2 -function is a function $f : X \longrightarrow R$ that is square integrable), the discrete wavelet transform (DWT) approach represents the time record x_n using a linear combination of basis functions $\phi_{J,k}$ and $\psi_{J,k}$.

[1] $x(t) = \sum_k S_{J,k}\, \phi_{J,k}(t) + \sum_k d_{J,k}\, \psi_{J,k}(t) + \sum_k d_{J-1,k}\, \psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\, \psi_{1,k}(t)$

where $S_{J,k}$, $d_{J,k}$,..., $d_{1,k}$ are the wavelet coefficients; J is a small natural number which depends mainly on N and the basis function; and k ranges from 1 to the number of coefficients in the specified component. The basis for the above decomposition is formed from the mother wavelet $\psi(t)$ and father wavelet $\phi(t)$ by translating in time and dilating in scale. Equations 2 and 3 show the mother and father of wavelet. .

[2] $\psi_{j,k}(t) = 2^{-\frac{j}{2}}\, \psi(2^{-j}t - k)$ $\quad j , k \epsilon Z$

[3] $\phi_{j,k}(t) = 2^{-\frac{j}{2}}\, \phi(2^{-j}t - k)$ $\quad j , k \epsilon Z$

where k = 1,2,...., N/2, in which N is the number of data record; j = 1,2,..., J, in which J is a small natural number; Z is the set of integers [Yi et al., 2012].

Wavelet denoising has three main steps including: (1) decomposition of input noisy signals into several levels of approximation and details of coefficients, using the selected wavelet basis. (2) Thresholding of coefficients which means to extract the coefficient containing the real signal and discard the others. (3) Reconstruction of the signal using approximation and details coefficients by use of the inverse wavelet transform [Yi et al., 2012].

In the wavelet based denoising procedure, the following parameters should be defined based on the type of measured signal: (1) threshold selection, (2) type of threshold (soft or hard), (3) multiplicative threshold rescaling, (4) wavelet type, (5) level of decomposition. The SNR is calculated in Equation 4 as.

[4] $$\text{SNR (dB)} = 10\log\frac{\sum_{k=1}^{N} x^2(k)}{\sum_{k=1}^{N}[x(k)-x'(k)]^2}$$

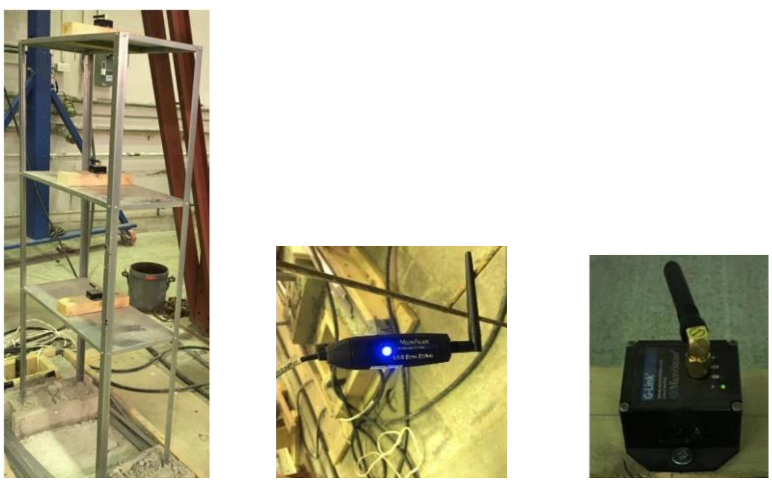
where x'(k) is the denoised signal and x(k) is the original signal. The constant N is the number of samples. The Root Mean Square Error is formulated in Equation 5.

[5] $$\text{RMSE} = \sqrt{\frac{\sum_{k=1}^{N}[x(k)-x'(k)]^2}{N}}$$

3 CASE STUDY

3.1 Three-story steel frame structure

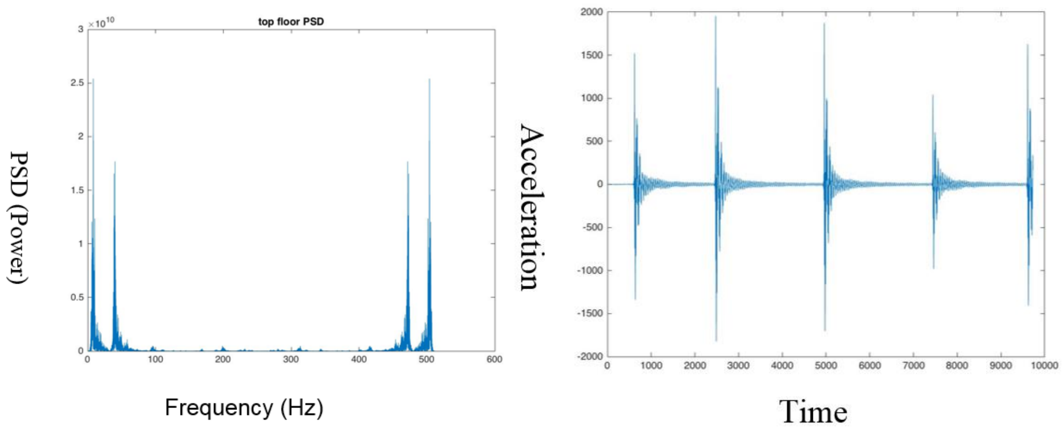
A scaled three story galvanized steel frame is used with 60 cm width, 2 cm depth and 133 cm height in total. Three MEMS wireless accelerometer sensors are installed in each floor to measure the free vibration with impact hammer force. The structure has been built and tested in the Structures Laboratory at Concordia University [Sabamehr et al., 2016]. The structure and instruments details are shown in Figure 2.



(a) (b) (c)

Figure 2: (a) Three story frame details (b) data acquisition (c) Wireless node

The collected data from the sensors have been considered as an original signal and additive white Gaussian noise (AWGN) is added to the signal. Then, two different denoising methods are applied to compare their accuracy in various SNRs. In this study, two common types of wavelet are used for denoising in two levels of decompositions. It should be noted that the adjustment of rescaling using a single estimation of level noise based on first-level coefficients and heursure threshold selection [Yie et al. 2012] are the same in all types. Figure 3 shows the collected data and its PSD in top floor of the structure.



(a) (b)

Figure 3: (a) top floor acceleration data in 19 second with 512 Hz sampling rate (b) Top floor PSD

The SNR after adding white Gaussian noise (SNR0) is varied between -10 dB to 40 dB by changing the noise variance. The SNR is calculated after denoising by wavelet db4 and sym8 algorithms [Yie et al. 2012] in 1 and 4 level of decompositions and low pass filter. The details of SNR in each floor are shown in Figure 4.

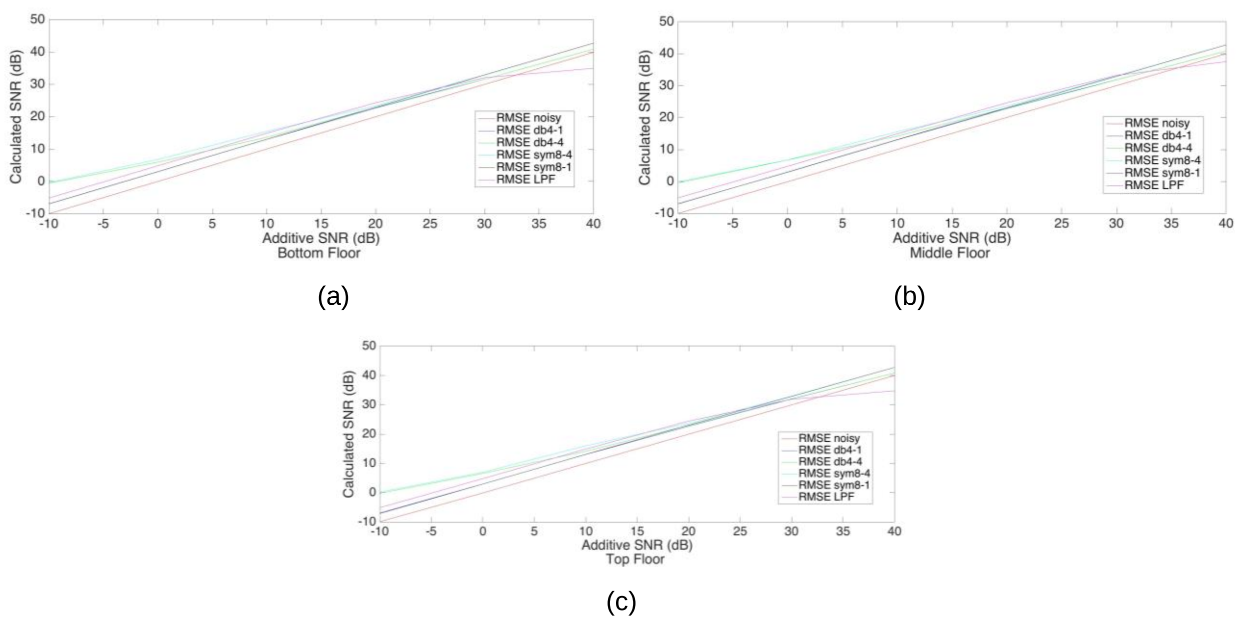
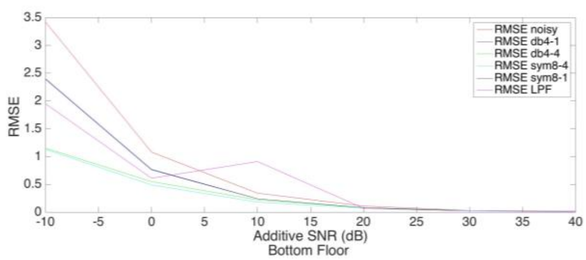
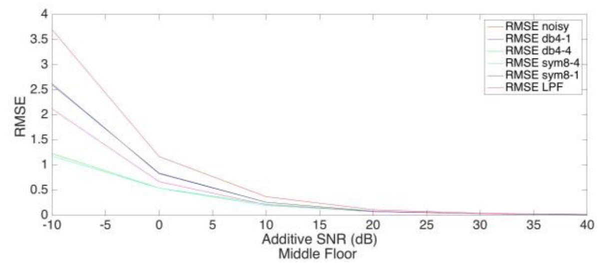


Figure 4: SNR after denoising versus SNR before denoising for (a) bottom floor (b) middle floor (c) top floor

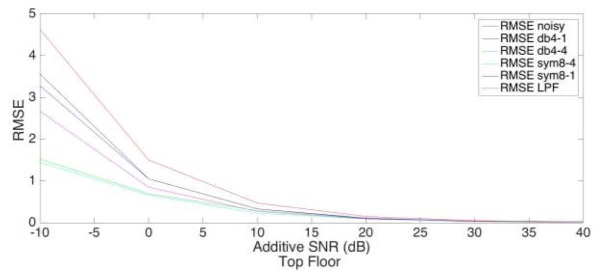
Another parameter that has been considered is Root Mean Square Error (RMSE). Figure 5 shows the variation of RMSE in three floors by use of different denoising techniques.



(a)



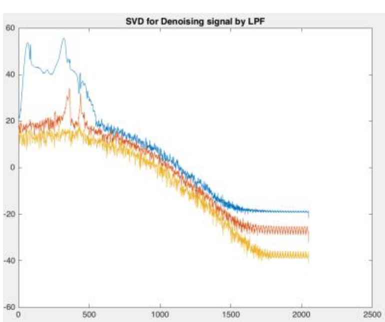
(b)



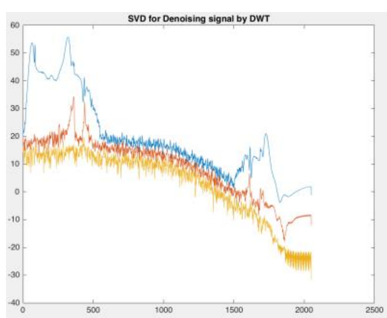
(c)

Figure 5: (a) RMSE in bottom floor (b) RMSE in middle floor (c) RMSE in top floor

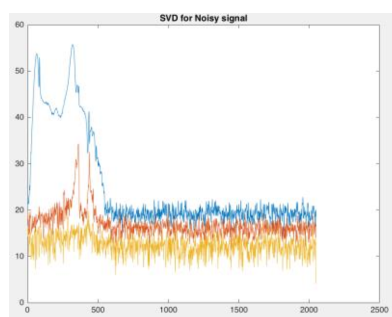
To find the effect of denoising signal in Singular Value Decomposition (SVD), the combination of Low pass filter, discrete wavelet transforms and noisy signal with SVD are compared together in top floor measured data with additive 20dB white Gaussian noise. The type of DWT is fourth order Daubechies (db4) with 4 level decompositions.



(a)



(b)



(c)

Figure 6: SVD values for noisy and denoised data

To calculate SVD, the Power Spectrum Density (PSD) of each floor should be computed, the output from PSD assembles the matrix to find the SVD in each frequency. As mentioned in [Brincker et al. 2015], the difference between maximum peak and the minimum singular value indicates the SNR value in each frequency. The difference is shown in Table 1 for first ten frequencies.

Table 1. SVD difference in Noisy and Denoising measured data

Frequency (Hz)	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00
SNR Difference in Noisy signal	71.73	101.44	67.78	68.22	75.31	73.00	95.98	165.76	169.52	144.90
SNR Difference in Denoising signal by DWT	71.66	101.47	67.76	68.10	75.25	73.10	96.03	165.85	169.40	144.88
SNR Difference in Denoising signal by LPF	71.67	101.48	67.77	68.14	75.30	73.06	96.10	165.77	169.41	144.90

4 CONCLUSION

The results show that Wavelets with fourth order Daubechies (db4) and eighth order of Symlets (sym8) algorithms achieve better result rather than Low pass filter. On the other hand, low pass filter gives better result than both types of wavelets when only one level of decomposition is used for data corresponding to each floor. The computed SNR of the data denoised using db4 and sym8 wavelets with four levels of decompositions produces accurate output in comparison to low pass filter and other types of wavelets in most additive SNRs. Moreover, low pass filter worked more efficiently than the single level decomposition of wavelets. Apart from this, the differences in SVD for multi-channel data are found to be insignificant. Filtering before SVD is not effective in band due to the fact that SVD is able to separate the signal and noise from each other, where the peak values are related to the signals and the minimum values indicate noise. But, denoising the data before applying SVD yields better results for out of band data, which is more effective in time domain methods rather than frequency domain as a frequency domain method needs the peak in spectral density, while the correlation of all data is considered in a time domain method.

5 ACKNOWLEDGEMENT

The support of the Natural Sciences and Engineering Research Council of Canada (NSERC) and IC-IMPACTS Network of Centres of Excellence is gratefully acknowledged.

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